Metric Mapping and Topo-metric Graph Learning of Urban Road Network

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***Abstract*— A road map serves as a model of the road network, which is especially desired for a vehicle performing autonomous navigation in urban road environment. This paper first introduces a metric mapping algorithm for urban roads, which generates an occupancy grid map of road surfaces and boundaries. Based on the metric map, we further propose an approach to extract a topo-metric graph which captures both topological and metric information of the road network. As a detailed model of the urban roads, the metric map can be used for obstacle avoidance and local path planning, while the topo-metric graph as a compact representation that can be used for some high-level reasoning processes. Our proposed algorithms are tested in real experiments, and have shown good results.**

I. Introduction

A. Road Mapping

Terrain Traversability Analysis (TTA) is one fundamental requirement for an outdoor robot to navigate safely and efficiently in its environment. The traversability property of certain terrain is defined as the level of difficulty for a robot to navigate it. A traversability map storing the traversability property of the whole environment is often desired, which can be used for path planning and other purposes [1], [2]. For autonomous vehicles moving on urban roads, the TTA problem becomes the problem of road detection, where road surfaces are safe areas to navigate, while road boundaries are forbidden places. In this sense, the traversability map can be replaced by a map of road surfaces and boundaries, which can be used to guide vehicle navigation.

This paper presents a probabilistic method for global road mapping, based on road detection and vehicle localization from our previous work [3], [4]. In our previous work, we use a tilted-down LIDAR to extract road surfaces and boundaries. By utilizing vehicle localization, the road detection results can be registered into a global coordinate, and fed into an Occupancy Grid Mapping (OGM) for the map building purpose. The output of our method will be a metric occupancy grid map, with the value of each grid representing its likelihood of being road surface or boundary.

B. Topo-Metric Graph

This metric map gives a detailed model of the road environment, with which an autonomous vehicle can generate a smooth and efficient path to follow. However, since this map only concerns about the occupancy of individual grids, it doesn't explicitly capture the overall structure of urban road network, and hence is not able to support high-level reasoning and analyses [5].

For this reason, we introduce a topo-metric representation to capture the road structure information, based on the idea of topological map. Topological map is a graph representation of the environment, with its nodes representing distinct places and edges showing their connectivity. Indeed, urban road environment has the most distinct topological structure, where its nodes can be intersections while edges are road links connecting them. While a vanilla topological map only concerns connectivity between nodes, we try to add metric flavour onto it. For each node (intersection), we will not only store its information of connected edges, but also record its position and covering area; for each edge (road link), besides its connectivity information, we use cubic spline fitting to get its mathematical representation, and keep the road width information at the same time. The topo-metric graph of urban roads will be learned from the metric occupancy grid map, serving as a compact complementary representation for the robot environment. This topo-metric representation of road network can be used not only for efficient path planning, but also for some high-level reasoning purposes such as semantic learning.

C. Related Work

Researches of road network extraction mainly come from the aerial remote sensing community, where people use high-resolution camera (or LIDAR) images for road detection. Baumgartner et al. [6] present a multi-resolution approach for automatic road extraction from digital aerial imagery. They use high-resolution image for edge detection and low-resolution image for line extraction. Hypotheses of roadsides are then generated with both resolution levels and explicit knowledge about roads. Based on the result of roadside extraction, road links and intersections can be finally constructed. In another work [7], Zhang et al. achieve road network extraction using mathematical morphology. Their approach first classifies the image to find road regions, and then uses morphological opening operation to erase the noise where irrelevant objects have the similar spectral characteristics as road surfaces. In some other researches, vehicle trajectories are collected for road network learning. Shi et al. [8] use massive GPS trajectories of vehicles for road network learning. A road network bitmap is first generated given the GPS data set, then the road skeleton is extracted from the bitmap, and finally graph extraction is applied to the skeleton to generate a vector map of road network.

In this paper, we first present a probabilistic road mapping

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method using a grounded vehicle, with a metric occupancy grid map generated for the road environment. Based on the metric map, we also extract a topo-metric graph for the roads. Compared to methods relying on aerial remote sensing, our method provides a ground way to extract road network, which could be less expensive and more accurate. While the methods using vehicle GPS trajectories can construct the rough structure of road network, they are not suitable for accurate metric mapping, and hence fail to capture some useful metric information like road width. In contrast, our approach can generate a detailed occupancy grid map of the road environment, which captures all the metric information. Since our topo-metric graph is learned from this grid map, its metric information can be well inherited.

The rest of paper is organized as follows. Section II describes the probabilistic method of metric mapping. Section III introduces the learning of topo-metric graph. The experimental results and analyses are shown in Section IV. Section V concludes the paper.

II. Metric Mapping

In this section, we will first briefly introduce the road detection algorithm from our previous work, then introduce probabilistic road mapping based on the detection results.

A. Road Detection

Road detection is one fundamental requirement to achieve road mapping. Here we use our previous work in [3] for road surface and boundary detection. A tilted-down LIDAR is mounted at the front a vehicle to accumulate a 3D representation of the road environment as the vehicle moves. Given the fact that surface curvature at the middle of road is usually smaller than that at the boundary, a region-growing method can be applied to extract the road surfaces as well as boundaries. The output of the road detection algorithm will be a point-cloud of road surfaces, and a point-cloud of boundaries. Both point-clouds are extracted in the vehicle attached coordinate system.

B. Road Mapping

In this part, a probabilistic framework is proposed for global road mapping, with road detection results from above. A global road map can not only be used for vehicle path planning, but also provide contextual information for vehicle localization and other perception purposes [9], [10].

Occupancy Grid Mapping (OGM) [11] is used for this mapping purpose. An occupancy grid map is a map that represents a map of environment by evenly spaced grids. Each grid represents a variable to be estimated. When vehicle poses are known, the road mapping problem is simplified from a Simultaneous Localization and Mapping Problem (SLAM) to an OGM problem, which is to estimate the posterior over map given the data: $p(m|z_{1:t}, x_{1:t})$, where m is the map, $z_{1:t}$ is the measurement from time 1 to t, and $x_{1:t}$ is the set of vehicle poses from time 1 to t. By assuming the independence between grids, the posterior can be further factored into $p(m|z_{1:t}, x_{1:t}) = \prod_i p(m_i|z_{1:t}, x_{1:t})$, where m_i denotes a grid cell in map m [11]. An inverse sensor model $p(m_i|z_t, x_t)$ is needed for above estimation process.

We rely on our localization algorithm for vehicle pose estimation [4]. This algorithm utilizes a synthetic LIDAR and odometery system for vehicle localization, which achieves centimeter-level accuracy. Given vehicle poses from the localization algorithm, the road mapping problem becomes an OGM problem of estimating $p(m|z_{1:t}, x_{1:t})$. In our application, m_i is a binary variable with two possible values, road surface and road boundary; z_t is the extracted road surface and boundary points in the vehicle attached coordinate system ("Baselink") at time t; x_t is the vehicle pose in the global coordinate ("map"). The extracted points z_t can be transformed into "map" coordinate given the knowledge of x_t . We have $p(m_i|z_t, x_t) = p(m_i|z_{t_i})$, where z_{t_i} is the point that falls into grid m_i. The inverse sensor model is defined as:

$$p(m_i = road\_surface|z_{t_i} = surface\_point) = k_1,$$
$$p(m_i = road\_surface|z_{t_i} = boundary\_point) = k_2,$$

where k_1, k_2 are parameters to be selected in experiments. Generally k_1 should be larger than $(1 - k_2)$, reflecting the fact that there are more noise in boundary points than that in surface points. This noise may come from false-positive boundary points, or temporal boundary points caused by vehicles or pedestrians. Given the inverse sensor model, a Static Bayes Model is applied to calculate the posterior $p(m|z_{1:t}, x_{1:t})$.

The output occupancy grid map can be converted into an 8-bit grayscale image, where the image describes the occupancy state of each cell of the world using the brightness of its corresponding pixel. Whiter pixels correspond to road surface, darker ones are road boundaries, while pixels in between are unknown area. The map origin is the same with the origin of vehicle localization, which is self-defined. The resolution of the map is selected by trading off map accuracy and computational cost.

III. Topo-metric Graph Learning

In this section, we will introduce the basic idea of topo-metric graph, and the method to learn it from the metric map. To learn the topo-metric graph, we first perform skeletonization on the metric map to extract road skeleton, then recover the topological structure of graph with the skeleton, and finally learn the metric properties of graph nodes and edges.

A. Topo-metric Graph

The topo-metric graph is designed to capture both topological and metric information of road network. It mainly consists of nodes and edges, which have both topological and metric attributes. The definition of the topo-metric graph can be found in Tab.1.

From the topological aspect, each node will maintain the IDs of its connected edges, and vice versa. This topological connectivity between nodes and edges captures the basic

TABLE I

TOPO-METRIC GRAPH DEFINITION

Objects	Attributes
Graph	{nodes, edges}
Node	{edge IDs, position, covering area}
Edge	{node IDs, shape spline, road width}

structure of the road network. From the metric aspect, the graph maintains its metric information via different metric attributes of nodes and edges. As shown in Tab.1, a node will keep a record of its position and covering area, while an edge will have a spline representation for its shape, together with its related road width.

B. Road Skeletonization

To learn the topo-metric graph, road skeleton needs to be first extracted via a skeletonization process. Skeletonization is a technique to extract skeleton from a digital binary image, which is a common pre-processing operation in raster-to-vector conversion.

A binary image of road surface is required for the skeletonization operation, which can be obtained by processing the metric map. As introduced in Section II, we get an 8-bit grayscale image as the occupancy grid map. Since the pixels of road surfaces usually have higher brightness, we can get the required binary image by properly thresholding the grayscale map, where white pixels of road surfaces will form the foreground object, while dark pixels of road boundary and gray pixels of unknown areas will become the background.

However, due to noise from the road detection process, the binary image may not be perfect, with holes appearing in the centre of road, or protruding spurs at the sides. The holes appear where no enough surface points have been extracted at certain grids of places, leaving their probability as “road surface” low. The spurs appear where road boundary points are wrongly classified as surface places, making related grids with falsely high belief as surface. Usually the sizes of spurs are bigger than those of the holes. Morphological transformations are applied to handle this problem. Since the holes are usually smaller than the spurs, we fill the holes using morphological closing with a smaller mask, and then remove the spurs using opening operation with a bigger one.

After the binary image is prepared, we apply skeletonization to extract the road skeleton. Image thinning method is employed for the skeletonization purpose, which have several beneficial properties: it preserves the shape and topology of the original object, and forces the skeleton being in the middle of the object. While there are many image thinning algorithms from the computer vision community, we choose the two-subiteration thinning algorithm in [12], which produces a single-pixel width skeleton with few redundant pixels.

C. Topological Structure Learning

The skeleton obtained from previous subsections capture the topological and shape information of the road network, based on which our topo-metric graph is constructed. This subsection introduces the learning for the topological structure based on the road skeleton.

After skeletonization using image thinning, we get a single-width skeleton with a few redundant pixels. A redundant pixel is defined as a pixel in the skeleton, which is not an endpoint, the deletion of which does not disconnect the skeleton. In an ideal case where a skeleton has no redundant pixels, a pixel from a road link should have no more than two connected neighbours, while a pixel at one intersection should have three or more. This provides us a method to distinguish between edge pixels and node pixels, if redundant pixels can be removed from the skeleton.

To remove the redundant pixels, we iterate through all the pixels of the skeleton except for the endpoints, and put them into a checking process. In the checking process, the pixel under examination is first turned off and a connected-component analysis is performed on its 8-connetion neighbours. If there is one connected-component formed by the 8 neighbours, then this pixel is a redundant pixel to be removed.

Given the minimal skeleton with no redundant pixels, we can easily build the topological structure of the road network. We first extract intersection pixels which have three or more neighbours, and store them as the nodes of our topo-metric graph. Then the intersection pixels are deleted from the skeleton, decomposing the skeleton into disconnected road links. These road links will serve as edges of the topo-metric graph. In the end, the connections between nodes and edges are constructed.

It should be mentioned that because of the sensitivity to noise, road skeletonization may generate fake spurs of the skeleton, which may further lead to spurious road links and intersections. For this reason, a filtering process is applied after the learning of topological structure, and road links whose length is smaller than a given threshold is discarded. After this, an intersection with no more than two road links is also removed.

D. Metric Property Learning

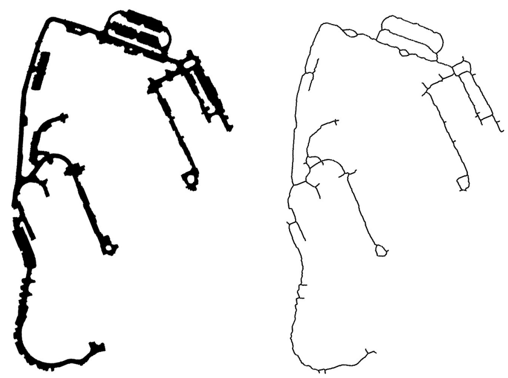
In this subsection, metric properties of the topo-metric graph will be learned. For an intersection, the metric properties include its position and its covering area. For a road link, the metric properties include a spline representation of its shape, and the average road width. It should be clarified that these metric properties are learned in the image coordinate of the metric map, and can be easily transformed into real-world global coordinate given the map’s origin and resolution.

Road links are the most fundamental components of a road network. While a road link is originally extracted as a string of connected pixels, we want to have a compact mathematical representation for it. As inspired by the work of Hasberg in [13], we use spline curves to model each road link. Cubic spline is chosen to guarantee that a road link has continuous

Fig. 1. Autonomous vehicle testbed

(a) Occupancy Grid Map (b) Road map overlaid on satellite image

Fig. 2. Road mapping results



(a) Binary image (b) Road skeleton

Fig. 3. Road Skeletonization

curvature. We use chord length parameterization to guarantee that the parameterization is proportional to the road length. Least Square fitting technique is applied to get an optimal spline given the input pixels. The cubic spline incorporates the shape information of a road link, which is compact and precise, and can be easily used for mathematical analyses. Besides a cubic spline, another metric property of a road link is its width. We assume that a road link should have uniform width, and approximate it with the average value of widths measured at different places.

An intersection is a junction of three or more road links. Its position and covering area are of vital importance for vehicle navigation. We define the position of an intersection to be the actual position of the intersection pixel, and its covering area to be a circle centred at this position, with the diameter as the biggest width of its connected road links. Given the image coordinate of the intersection pixel, to determine the intersection position and covering area is trivial.

IV. Experiments

A. Experiment Setup

Our proposed methods are tested in real experiments. Our test bed is a Yamaha G22E golf cart with autonomous driving ability [14], as shown by Fig. 1. The sensors that our tests mainly rely on are the tilted-down LIDAR (SICK LMS-291) and the vehicle's odometry system. As the prerequisite functions for our metric mapping algorithm, road detection and vehicle localization can be realized with the LIDAR and the odometery system. The LIDAR is mounted at the front, with height of $1.73\,m$ and tilted-down angle of 12 degree. The calibration of the LIDAR is performed manually beforehand. The odometry system is mainly composed of an IMU MicroStrain 3DM-GX3-25 mounted at the center of the rear axis, and two wheel-encoders at the sides of rear wheels. Our experiments are conducted in Engineering Campus, National University of Singapore.

B. Experimental Results

The first experiment is about metric mapping. To generate the road map, our vehicle is driven around the Engineering Campus for 3 rounds with vehicle localization and road detection running. The localization algorithm helps to transform road detection results in the global "map" coordinate, and the transformed road detection results are used to estimate one occupancy grid road map. For the inverse sensor model, k_1 and k_2 are chosen to be 0.9 and 0.2 respectively. Fig. 2 shows results of road mapping. The left figure shows one Occupancy Grid Map of the surveyed road with an area of $429\,m \times 475\,m$. Its resolution is 0.1 $m/pixel$. Thanks to the localization algorithm we use [4], the map can be georeferenced. Hence we are able to overlay the road surface on a satellite map for comparision, as shown in the right figure. It can be seen that the proposed algorithm mapped out the driven road with good accuracy.

Based on the metric map, topo-metric graph of the road network is constructed. In the first step, skeletonization is performed to extract the medial axis of road surface, as shown in Fig. 3. Binarization is applied to the grayscale metric map with a proper threshold value, followed by the morphological operations of closing and opening to get a binary image of road surface. Skeletonization of road surface is performed with the image thinning technique, and a road skeleton of single-pixel width can be extracted. In the second step, topological structure of road network is learned from the skeleton, as shown in Fig. 4. Road links are drawn with blue lines, and the intersections are marked by red circles. While image thinning is sensitive to noise and may generate spurs of the skeleton, we apply a filtering process to remove the branches whose length is smaller than certain threshold.

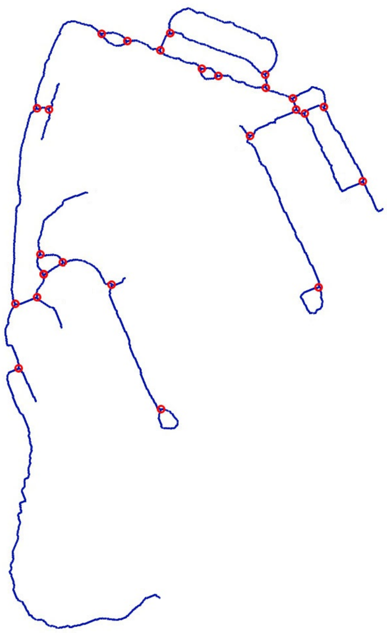


Fig. 4. Road topological structure

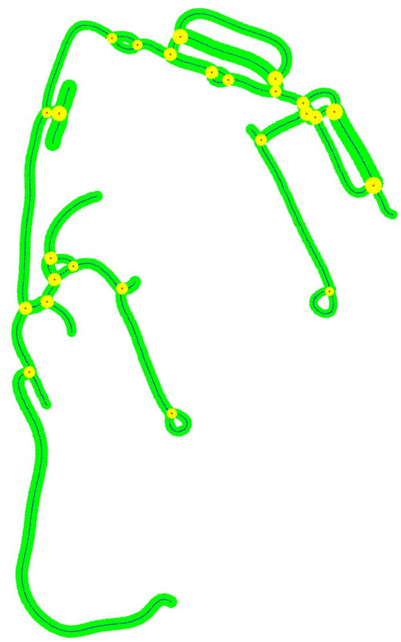


Fig. 5. Topo-metric graph visualization

In the final step, metric properties of the road network are learning, including road shape and width, and also positions and covering areas of the intersections. The topo-metric graph is visualized in Fig. 5, where each edge is visualized as a thick spline with the width of its corresponding road, and each intersection is marked by a yellow circle of its covering area. Compared to the satellite map and the occupancy grid map in Fig. 2, it can be seen that the topo-metric graph recovers the road network quite well, both for its topological structure, and for its metric properties like road shape and width.

V. CONCLUSIONS AND FUTURE WORK

This paper introduces a metric mapping algorithm for urban roads, as well as an approach to build a topo-metric graph of the road network. Our proposed algorithms are tested in real experiments, and show good results. In our future work, we will concentrate on using the metric map and topo-metric graph for efficient global path planning and semantic reasoning.

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